Journal of Sustainable Economy

Journal homepage: https://scholarsin.com/journals/sustainable-economy

Quantifying The Impact of Kinetic Control, Catalyst Performance, and Feedstock Purity on Integrated Polyethylene Reactor Performance

Saleh Abdul Hamid Saleh Ben Hamid[1] and Omar Emad Hassouna[1]

[1]*School of Engineering, Alfa University College, Selangor, Malaysia*

ABSTRACT

The operational reliability of Air Conditioning and Refrigeration (AC/R) systems in employee-occupied service facilities is critical for maintaining personnel comfort, safeguarding sensitive electronic equipment, and ensuring uninterrupted industrial operations in hydrocarbon processing environments. This quantitative study examines the factors affecting AC/R system reliability at the Ras Lanuf Oil and Gas Processing Company (RASCO) in Libya, operating under extreme desert conditions with ambient temperatures exceeding 45°C, pervasive sand and dust particulates, and atmospheric salinity. Grounded in Reliability Engineering Theory and the Bathtub Curve model, the research evaluates three controllable operational variables: refrigerant selection, compressor maintenance practices, and coil/filter maintenance protocols. Using a structured survey instrument administered to 85 engineering and technical personnel across RASCO's service facilities, data were analyzed through descriptive statistics, Pearson correlation, and multiple linear regression. Results demonstrate that all three factors significantly influence operational reliability, with compressor maintenance practices emerging as the strongest predictor ($\beta = 0.358$, $p < 0.001$), followed by coil/filter maintenance ($\beta = 0.312$, $p = 0.001$), and refrigerant selection ($\beta = 0.284$, $p = 0.002$). The regression model explained 64.3% of the variance in operational reliability ($R^2 = 0.643$, $F(3,81) = 48.62$, $p < 0.001$). These findings provide empirical validation for transitioning from reactive maintenance to condition-based predictive strategies, implementing adaptive weather-responsive cleaning schedules, and establishing standardized refrigerant management protocols. The study contributes to bridging the research gap between HVAC engineering and industrial reliability theory in extreme climate contexts, offering actionable insights for facility managers to optimize system uptime, reduce lifecycle costs, enhance energy efficiency, and maintain safe working conditions in desert industrial environments.

Keywords: Operational reliability, air conditioning systems, refrigeration systems, predictive maintenance, desert environment, compressor reliability, heat exchanger fouling

[1] Corresponding author.
Email address: omar.i@alfa.edu.my (Omar Emad Hassouna)

Received 1 Jun 2026; Received in revised form 13 July 2026; Accepted 27 July 2026
Available online 31 July 2026
ISSN: 0231-2618/

1. Introduction

The global polyethylene (PE) market remains an indispensable foundation of the modern petrochemical industry, providing the essential thermoplastic materials required for international packaging, infrastructure, construction, automotive, and consumer goods manufacturing. To satisfy global demand, industrial petrochemical complexes operate high-capacity, continuous gas-phase fluidized bed reactors—most notably based on the UNIPOL™ process technology—to synthesize commodity polyolefins with tight resin property specifications (Fan et al., 2023). In these highly integrated polymerization systems, maintaining consistent product quality metrics, such as Melt Flow Index (MFI) and resin density, while maximizing throughput productivity represents a continuous engineering challenge. Fluidized bed gas-phase reactors operate under highly dynamic, exothermic conditions where small operational disturbances can induce localized thermal hot spots, bed agglomeration, polymer sheeting, and severe reactor fouling, ultimately forcing costly unscheduled shutdowns (Ghasem, 2024). Stable polymerization depends fundamentally on regulating reaction kinetics—specifically managing the hydrogen-to-ethylene gas ratio to control chain transfer and polymer molecular weight—while simultaneously feeding highly active catalyst systems (Bi et al., 2025; Yang et al., 2025). However, the operational integrity of the polymerization process is profoundly vulnerable to trace chemical impurities in the monomer and co-monomer feed streams. Minute quantities of catalyst poisons, such as oxygen, moisture, carbon monoxide, carbon dioxide, and acetylenic compounds, deactivate active transition-metal catalytic sites, alter polymer chain architecture, degrade physical resin properties, and cause substantial economic losses (Hernández Fernández et al., 2025; Kusenberg et al., 2022). In major industrial plants such as the Ras Lanuf Oil and Gas Processing Company in Libya, these technical challenges are further compounded by operational pressures to maintain high plant availability, maximize catalyst yield, and optimize capacity utilization to remain globally competitive.

Although extensive chemical engineering research has evaluated polyethylene reactor dynamics, catalyst formulation chemistry, and poison deactivation mechanisms in laboratory or computational settings, a significant empirical problem persists in plant operations. Existing scholarship predominantly models kinetic control, catalyst activity, and feedstock impurities as isolated, deterministic physical parameters analyzed via dynamic computer simulations (Ghasem, 2024; Fan et al., 2023) or laboratory-scale experiments (Hernández Fernández et al., 2025; Nazarloo et al., 2024). Consequently, current literature lacks a holistic, validated empirical model that quantifies how expert plant personnel—including process engineers, operations staff, and R&D chemists—perceive and integrate Kinetic Control Efficacy (KCE), Catalyst System Performance (CSP), and Feedstock Purity Management (FPM) to influence overall Integrated Reactor Performance (IRP). Without such an integrated model, petrochemical facility managers at Ras Lanuf cannot determine whether observed operational performance gaps or off-specification resin batches stem primarily from kinetic control instabilities, suboptimal catalyst activity, or feedstock contamination, leading to reactive, trial-and-error decision-making. To resolve this operational problem, this study formulates three primary research questions: (1) What are the perceived levels of Kinetic Control Efficacy (KCE), Catalyst System Performance (CSP), Feedstock Purity Management (FPM), and Integrated Reactor Performance (IRP) among technical personnel at the Ras Lanuf polyethylene plant? (2) What is the nature, strength, and direction of the relationships existing among KCE, CSP, FPM, and IRP? (3) What is the unique and relative contribution of KCE, CSP, and FPM in predicting Integrated Reactor Performance (IRP)? Correspondingly, the overarching aim of this research is to formulate and empirically validate a quantitative predictive model: IRP = f(KCE, CSP, FPM). The specific research objectives are: (RO1) to assess the perceived levels of KCE, CSP, FPM, and IRP at Ras Lanuf; (RO2) to evaluate the bivariate relationships among the independent variables and IRP; and (RO3) to determine the unique predictive power of each independent variable on overall reactor performance. Based on reaction engineering and catalysis theory, three main hypotheses are developed: H1 posits that Kinetic Control Efficacy has a significant positive relationship with Integrated Reactor Performance; H2 posits that Catalyst System Performance has a significant positive relationship with Integrated Reactor Performance; and H3 posits that Feedstock Purity Management has a significant positive relationship with Integrated Reactor Performance.

The practical and academic contributions of this study are substantial. Practically, this research equips Ras Lanuf management with an empirically validated diagnostic framework to strategically prioritize capital investments and operational workflows—whether focusing capital on feed purification beds, catalyst vendor optimization, or automated kinetic control systems—thereby reducing off-spec production, mitigating unscheduled reactor shutdowns, and supporting Libya's downstream petrochemical development. Academically, this study bridges chemical reaction engineering with socio-technical management theory by translating complex thermodynamic, catalytic, and chemical processes into validated multi-item operational constructs, offering a novel perception-based diagnostic methodology for process plant performance. For the purpose of this study, Kinetic Control Efficacy (KCE) is operationally defined as the perceived effectiveness of automated control systems and operational procedures in maintaining stable reaction rates, reactor temperature uniformity, and precise hydrogen/ethylene and co-monomer ratios (Ghasem, 2024). Catalyst System Performance (CSP) refers to the perceived overall activity, selectivity, mechanical stability, and productivity of the active catalyst system under actual operating conditions (Yang et al., 2025). Feedstock Purity Management (FPM) represents the perceived rigor and effectiveness of feed purification, online impurity monitoring, and supplier quality control in eliminating catalyst poisons from monomer feed streams (Kusenberg et al., 2022; Hernández Fernández et al., 2025). Integrated Reactor Performance (IRP) is defined as a holistic measure of reactor output combining resin quality consistency (MFI and density) with plant productivity metrics (throughput, catalyst yield, and operational uptime).

2. Literature Review

The manufacturing of polyolefins within gas-phase fluidized bed reactors involves a highly complex interplay of multi-phase fluid hydrodynamics, heat and mass transfer, and polymerization reaction kinetics. Polymerization reaction engineering theory establishes that chain growth proceeds through elementary chemical steps: active site formation, chain initiation, chain propagation, chain transfer to hydrogen or monomer, and chain termination (Ghasem, 2024). The structural characteristics of the resulting polyethylene resin—specifically average molecular weight, molecular weight distribution (MWD), and short-chain branching distribution—are directly governed by reactor operating conditions, including temperature, ethylene partial pressure, hydrogen-to-ethylene gas ratio (H_2/C_2H_4), and co-monomer (e.g., 1-butene or 1-hexene) concentration ratios. Because ethylene polymerization is strongly exothermic ($\Delta H \approx -93.6 \text{ kJ/mol}$), failure to rapidly dissipate heat from growing polymer particles results in localized thermal runaway, polymer melting, and massive bed agglomeration (Fan et al., 2023). Dynamic population balance modeling confirms that fluidized bed reactors are naturally non-linear and prone to operational oscillations when catalyst feed rates or gas recycle cooling loops experience disturbances (Ghasem, 2024). Effective kinetic control systems utilizing advanced Proportional-Integral-Derivative (PID) or Model Predictive Control (MPC) algorithms are therefore essential to stabilize reaction rates, maintain uniform bed temperatures, and enable smooth transitions between different product resin grades.

Simultaneously, heterogeneous catalysis science establishes the chemical catalyst system as the primary engine driving polymerization efficiency. Modern polyethylene manufacturing utilizes three major catalyst families: titanium-based Ziegler-Natta catalysts, chromium-based Phillips catalysts, and single-site metallocene or post-metallocene catalysts (Yang et al., 2025). Ziegler-Natta catalysts possess multi-site active centers that produce broad molecular weight distributions suitable for pipe and blow-molding applications, whereas single-site metallocene catalysts feature uniform active centers yielding narrow MWD resins with superior optical and mechanical strength. Catalyst performance is evaluated through catalyst activity or yield ($\text{kg PE} / \text{g catalyst}$), comonomer incorporation efficiency, hydrogen response sensitivity, and thermal stability. Recent advances in artificial intelligence and machine learning demonstrate that gradient-boosted decision trees and artificial neural networks can accurately predict catalyst productivity and polymer MWD from ligand molecular descriptors (Yang et al., 2025). However, catalyst performance under actual industrial conditions often departs from theoretical laboratory predictions due to hydrodynamic non-idealities, particle attrition, and, most critically, chemical deactivation caused by feed stream poisons.

Feedstock purity management represents a critical protective barrier in polyolefin manufacturing. Polymerization catalysts are extraordinarily sensitive to chemical poisons present in trace concentrations (parts per million or parts per billion). Catalyst poisons are categorized as temporary (reversible) or permanent (irreversible). Reversible poisons, such as carbon monoxide and carbon dioxide, temporarily coordinate to active metal sites and retard polymerization rates without destroying the catalyst complex. In contrast, irreversible poisons—including water, oxygen, hydrogen sulfide, acetylenic hydrocarbons, and basic nitrogen compounds (e.g., amines)—react chemically with active transition-metal centers or organometallic co-catalysts (e.g., triethylaluminum, TEAL), causing permanent, irreversible deactivation (Hernández Fernández et al., 2025; Kusenberg et al., 2022). Computational Density Functional Theory (DFT) calculations confirm that amine compounds exhibit extremely high binding energies with Ziegler-Natta titanium sites, forming stable coordination complexes that completely block monomer access (Hernández Fernández et al., 2025). In industrial plants processing cracked naphtha or alternative recycled plastic pyrolysis feeds, contamination risks escalate dramatically, necessitating advanced feed purification systems consisting of de-oxygenation beds, alumina guard beds, and molecular sieve desiccant dryers (Kusenberg et al., 2022; Nazarloo et al., 2024).

A comprehensive synthesis of empirical literature from 2022 to 2026 highlights the advanced technical understanding of polyethylene production across computational, physical, and machine learning domains. Table 2.1 summarizes key empirical studies examining polyethylene reactor dynamics, catalyst performance, and impurity effects.

Table 2.1: Summary of Empirical Studies on Polyethylene Reactor Performance

N	Author(s) & Year	Methodology	Research Context	Key Variables Examined	Major Relevant Findings
1	Ghasem (2024)	Dynamic Simulation (Populat	Fluidized Bed Reactor for Ethylene	Catalyst feed rate, temperature	Demonstrated that reactor stability

N	Author(s) & Year	Methodology	Research Context	Key Variables Examined	Major Relevant Findings
		ion Balance Model)	Copolymerization	control, PID stability (KCE)	is extremely sensitive to catalyst injection rates; PID feedback control is mandatory to prevent thermal runaway.
2	Fan et al. (2023)	Computational Fluid Dynamics (CFD) & Scale-up	Gas-Phase Fluidized Bed Reactor Scale-up	Bed hydrodynamics, thermal distribution, hotspot formation (KCE)	Identified critical scale-up parameters required to ensure uniform gas distribution and avoid localized hot spots during capacity expansion.
3	Yang et al. (2025)	Machine Learning (Gradient Boosted Regression)	Ethylene Homopolymerization with FI Catalysts	Catalyst ligand structure, activity, MWD prediction (CSP)	Established that machine learning models can accurately predict catalyst

N	Author(s) & Year	Methodology	Research Context	Key Variables Examined	Major Relevant Findings
					activity and polymer MWD based on molecular structural descriptors.
4	Hernández Fernández et al. (2025)	Computational Chemistry (DFT & IR Spectroscopy)	Ziegler-Natta Catalyst Poisoning Mechanisms	Amine impurities, deactivation energy, active site blocking (FPM/CSP)	Quantified the strong coordination binding energies of amine impurities on titanium centers, proving permanent catalyst site destruction.
5	Kusenberg et al. (2022)	Systematic Review & Experimental Characterization	Pyrolysis Oil Feedstock from Waste Plastics	Contaminants (N, O, Halogens, Heavy Metals) in feed (FPM)	Detailed the severe, multi-stage poisoning effect of heteroatom impurities in recycled feeds on downstream steam

N	Author(s) & Year	Methodology	Research Context	Key Variables Examined	Major Relevant Findings
					cracking and polymerization.
6	Nazarloo et al. (2024)	Experimental Catalytic Pyrolysis & Fixed Bed	Waste LDPE Chemical Recycling	Catalyst deactivation rate, ex-situ reactor design (FPM/CSP)	Demonstrated that an ex-situ fixed-bed reactor configuration effectively traps volatile impurities, mitigating catalyst poisoning and boosting yield.
7	Bi et al. (2025)	Kinetic Modeling & Closed-Loop Experiment	Closed-Loop PE De-polymerization to Ethylene	Temperature-zone kinetic control, reaction rate optimization (KCE)	Proved that a kinetic-driven reactor control strategy (KDRC) maximizes monomer recovery yield while maintaining narrow product selectivity.

Crucially, the literature review reveals a clear academic research gap. Existing empirical studies rely almost exclusively on computer simulations (Ghasem, 2024; Fan et al., 2023), machine learning modeling (Yang et al., 2025), or bench-scale laboratory experiments (Hernández Fernández et al., 2025; Nazarloo et al., 2024). These technical studies isolate single variables under idealized conditions, ignoring the operational reality of commercial petrochemical plants where process control, catalyst activity, and feedstock purity operate simultaneously as an integrated socio-technical system. No empirical research to date has captured expert operational perceptions from plant engineers, supervisors, and chemists to model the joint impact of Kinetic Control Efficacy, Catalyst System Performance, and Feedstock Purity Management on holistic Integrated Reactor Performance. To bridge this gap, this study formulates an Integrated Conceptual Framework combining Reaction Engineering Principles, Heterogeneous Catalysis Theory, and Total Quality Management (TQM) principles. The framework posits that Integrated Reactor Performance (IRP) is a direct positive function of Kinetic Control Efficacy (H1), Catalyst System Performance (H2), and Feedstock Purity Management (H3). Figure 2.1 illustrates the conceptual model linking KCE, CSP, and FPM to IRP.

3. Method

This chapter presents the quantitative research methodology designed to empirically test the hypothesized relationships between Kinetic Control Efficacy (KCE), Catalyst System Performance (CSP), Feedstock Purity Management (FPM), and Integrated Reactor Performance (IRP) at the Ras Lanuf polyethylene plant. Grounded in a positivist research philosophy, this study assumes an objective reality that can be measured and analyzed through quantitative survey methods and deductive statistical hypothesis testing (Creswell & Creswell, 2018; Sekaran & Bougie, 2016). The research design is a quantitative, descriptive-correlational, cross-sectional survey. A survey-based approach capturing expert perceptions is explicitly chosen because latent operational constructs—such as control system stability, catalyst robustness, and feedstock quality management—involve professional human judgment and operational experience that cannot be captured purely through physical DCS sensor readings (Lavrakas, 2008; Saunders et al., 2019).

The target population comprised all technical and engineering staff possessing direct operational knowledge of the gas-phase polyethylene reactor at Ras Lanuf Company, Libya. The population included Process Engineers, Operations Supervisors and Staff, R&D Chemists, and Maintenance Engineers. Given the specialized and bounded nature of this professional group within a single manufacturing complex, a purposive sampling strategy was employed (Etikan et al., 2016). Official access was secured through Ras Lanuf plant management, establishing an accessible sampling frame of approximately 130 eligible technical personnel. Sample size adequacy was evaluated using Tabachnick and Fidell's (2019) multivariate regression rule ($N > 50 + 8m$, where $m = 3$ predictors), requiring a absolute minimum of 74 cases. Furthermore, statistical power analysis for multiple linear regression confirmed that a sample size of $N = 95$ achieves a statistical power exceeding 0.85 at $\alpha = 0.05$ for a medium-to-large effect size ($f^2 = 0.20$), providing ample power for hypothesis testing (Cohen, 1992). A total of 130 surveys were distributed via digital Google Forms and physical questionnaires, resulting in 95 completed, fully usable responses (73.1% response rate). Table 3.1 displays the research project timeline and Gantt chart.

Table 3.1: Research Project Gantt Chart and Operational Phases

N	**Project Phase / Operational Activity**	**Duration**	**March 2026**	**April 2026**	**May 2026**	**June 2026**	**July 2026**	**August 2026**
1	Phase 1: Research Preparation & Literature Review	4 Weeks						
2	Phase 2: Survey Instrument Development & Translation	5 Weeks						
3	Phase 3: Pilot Testing & Main Data Collection	5 Weeks						
4	Phase 4: Data Cleaning, Reliability & SPSS Regr	4 Weeks						

N	Project Phase / Operational Activity	Duration	March 2026	April 2026	May 2026	June 2026	July 2026	August 2026
	ession							
5	Phase 5: Thesis Writing, Discussion & Submission	8 Weeks					■	■

Data collection utilized a structured, self-administered questionnaire divided into five distinct sections: Section A captured demographic and professional background data; Section B measured Kinetic Control Efficacy (KCE, 7 items); Section C measured Catalyst System Performance (CSP, 7 items); Section D measured Feedstock Purity Management (FPM, 7 items); and Section E measured Integrated Reactor Performance (IRP, 7 items). All latent construct items utilized a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Scale content validity was established through an expert evaluation panel comprising two polymerization engineering professors, two senior industrial polyolefin process engineers, and a survey methodologist. Computing item and scale Content Validity Index (CVI) resulted in retaining only items with CVI ≥ 0.80 (Polit & Beck, 2006). Double-blind back-translation ensured conceptual equivalence between English and Arabic versions (Brislin, 1970). A pilot study conducted with 30 technical specialists from an adjacent petrochemical plant confirmed scale internal consistency, yielding Cronbach's alpha values exceeding the 0.70 benchmark (Nunnally & Bernstein, 1994). Exploratory Factor Analysis (EFA) confirmed construct validity with clean loadings > 0.50 on intended factors and cross-loadings < 0.30 (Fornell & Larcker, 1981).

Data analysis was executed sequentially using IBM SPSS Statistics (Version 28). Preliminary screening confirmed dataset completeness ($N = 95$), with univariate outliers checked via standardized z-scores ($\le \pm3.29$) and multivariate outliers evaluated using Mahalanobis distance at $p < 0.001$. Scale internal consistency was re-assessed using Cronbach's alpha (α). Bivariate Pearson correlation analysis (r) evaluated zero-order relationships, while Multiple Linear Regression (MLR) tested the predictive model $\text{IRP} = f(\text{KCE}, \text{CSP}, \text{FPM})$. Regression diagnostics confirmed parametric assumptions: residual normality (P-P plot and standardized residual histogram), linearity and homoscedasticity (residual scatterplots), error independence (Durbin-Watson = 1.88), and absence of multicollinearity (Variance Inflation Factor [VIF] < 5.0, Tolerance $>

0.20$) (Field, 2018; Keith, 2019). Ethical protocols strictly complied with academic standards: informed consent preceded the survey, complete participant anonymity was maintained without collecting employee IDs or IP addresses, data were securely stored on encrypted servers, and formal organizational research clearance was granted by Ras Lanuf management (Resnik, 2020).

4. Data Analysis

A total of 130 questionnaires were distributed to technical personnel at the Ras Lanuf polyethylene plant, yielding 95 completed and usable responses (73.1% response rate). Table 4.1 summarizes the survey response rate. Data screening confirmed zero missing values, while standardized z-scores (< ±3.29) and Mahalanobis distance parameters confirmed the absence of severe univariate or multivariate outliers, establishing a clean dataset for inferential testing.

Table 4.1: Summary of Survey Response Rate

Survey Response Status	Number of Questionnaires	Percentage (%)
Total Questionnaires Distributed	130	100.0%
Completed Questionnaires Received	95	73.1%
Incomplete / Excluded Questionnaires	0	0.0%
Valid Questionnaires Retained for Analysis	95	73.1%

The demographic and professional profile of the 95 respondents indicates a highly qualified, technically diverse sample. Gender distribution was nearly equal, comprising 48 males (50.5%) and 47 females (49.5%). Table 4.2 presents the gender breakdown. Professional experience in polyethylene or petrochemical operations showed a well-seasoned sample: 31.6% (n = 30) possess 7–10 years of experience, 25.3% (n = 24) have 3–6 years, 22.1% (n = 21) have less than 3 years, and 21.1% (n = 20) have more than 10 years of experience. Table 4.3 outlines experience levels. Age distribution revealed that 27.4% (n = 26) are aged 25–31 years, 26.3% (n = 25) are aged 32–38 years, 25.3% (n = 24) are aged 18–24 years, and 21.1% (n = 20) are aged 39–45 years. Table 4.4 presents age distribution. Educational attainment demonstrated strong academic backgrounds: 33.7% (n = 32) hold a Diploma/Technical Certificate, 29.5% (n = 28) hold a Bachelor's degree, 26.3% (n = 25) hold a Master's degree, and 10.5% (n = 10) possess a PhD or higher qualification. Table 4.5 details educational attainment. Current job roles were evenly balanced across operational and scientific functions: Operations Supervisors and Staff represented 38.9% (n = 37), R&D Chemists represented 38.9% (n = 37), and Process Engineers represented 22.1% (n = 21). Table 4.6 presents the breakdown by job role.

Table 4.2: Gender Distribution of Respondents

Gender	**Frequency (n)**	**Percentage (%)**
Male	48	50.5
Female	47	49.5
Total	95	100.0

Table 4.3: Years of Professional Experience in Polyethylene or Petrochemical Operations

Years of Experience	**Frequency (n)**	**Percentage (%)**
Less than 3 years	21	22.1
3–6 years	24	25.3
7–10 years	30	31.6
More than 10 years	20	21.1
Total	95	100.0

Table 4.4: Age Distribution of Respondents

Age Category	**Frequency (n)**	**Percentage (%)**
18–24 years	24	25.3
25–31 years	26	27.4
32–38 years	25	26.3
39–45 years	20	21.1
Total	95	100.0

Table 4.5: Highest Educational Level Attained

Educational Level	**Frequency (n)**	**Percentage (%)**
Diploma / Technical Certificate	32	33.7
Bachelor's Degree	28	29.5
Master's Degree	25	26.3
PhD or Higher	10	10.5
Total	95	100.0

Table 4.6: Current Job Role of Respondents

Job Role	Frequency (n)	Percentage (%)
Process Engineer	21	22.1
Operations Supervisor / Staff	37	38.9
R&D Chemist	37	38.9
Total	95	100.0

Construct internal consistency was evaluated using Cronbach's alpha coefficient (α). All four scales exhibited high reliability exceeding the 0.70 benchmark: Integrated Reactor Performance achieved $\alpha = 0.897$, Feedstock Purity Management achieved $\alpha = 0.875$, Catalyst System Performance achieved $\alpha = 0.855$, and Kinetic Control Efficacy achieved $\alpha = 0.838$. Table 4.7 presents the reliability analysis. Descriptive statistics evaluated construct central tendencies on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). All constructs recorded high mean scores above 4.05: Kinetic Control Efficacy recorded the highest mean ($M = 4.1218, SD = 0.65464$), followed by Catalyst System Performance ($M = 4.1098, SD = 0.70494$), Feedstock Purity Management ($M = 4.0842, SD = 0.75117$), and Integrated Reactor Performance ($M = 4.0617, SD = 0.75237$). Low standard deviations (< 0.76) indicate high response agreement. Table 4.8 presents construct descriptive statistics.

Table 4.7: Reliability Analysis of Measurement Constructs

Measurement Variable / Construct	Number of Scale Items	Cronbach's Alpha (α)	Internal Reliability Status
Kinetic Control Efficacy (KCE - IV1)	7	0.838	Good Reliability
Catalyst System Performance (CSP - IV2)	7	0.855	Good Reliability

Measurement Variable / Construct	Number of Scale Items	Cronbach's Alpha (α)	Internal Reliability Status
Feedstock Purity Management (FPM - IV3)	7	0.875	Strong Reliability
Integrated Reactor Performance (IRP - DV)	7	0.897	Strong Reliability

Table 4.8: Descriptive Statistics of Study Variables

Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Kinetic Control Efficacy (KCE - IV1)	95	1.86	5.00	4.1218	0.65464
Catalyst System Performance (CSP - IV2)	95	1.71	5.00	4.1098	0.70494
Feedstock Purity Management (FPM - IV3)	95	1.71	5.00	4.0842	0.75117
Integrated Reactor Performance (IRP - DV)	95	2.00	5.00	4.0617	0.75237

Pearson correlation analysis evaluated bivariate relationships among variables. Integrated Reactor Performance (DV) exhibited strong, statistically significant positive correlations with all three independent variables: Feedstock Purity Management ($r = 0.764, p < 0.01$), Kinetic Control Efficacy ($r = 0.703, p < 0.01$), and Catalyst System Performance ($r = 0.697, p < 0.01$). Inter-predictor correlations were also positive and significant, ranging from $r = 0.629$ (KCE–CSP) to $r = 0.848$ (CSP–FPM). Table 4.9 presents the Pearson correlation matrix.

Table 4.9: Pearson Correlation Matrix Among Study Variables

Variables	**1. KCE**	**2. CSP**	**3. FPM**	**4. IRP**
1. Kinetic Control Efficacy (KCE)	1.000			
2. Catalyst System Performance (CSP)	0.629**	1.000		
3. Feedstock Purity Management (FPM)	0.705**	0.848**	1.000	
4. Integrated Reactor Performance (IRP)	0.703**	0.697**	0.764**	1.000

*** Correlation is significant at the 0.01 level (2-tailed), N = 95.*

Multiple linear regression evaluated the joint predictive power of the independent variables on Integrated Reactor Performance. The overall model was statistically significant ($F(3, 91) = 54.477, p < 0.001$), explaining 64.2% of the total variance in reactor performance ($R^2 = 0.642$, Adjusted $R^2 = 0.631$). Table 4.10 presents the Model Summary and Table 4.11 presents the ANOVA results. Standardized regression coefficients (β) revealed that Feedstock Purity Management was the strongest positive predictor of reactor performance ($\beta = 0.419, t = 3.225, p = 0.002$), followed by Kinetic Control Efficacy ($\beta = 0.318, t = 3.580, p = 0.001$). Catalyst System Performance exhibited a positive but non-significant unique effect when controlling for KCE and FPM ($\beta = 0.142, t = 1.195, p = 0.235$). Table 4.12 details the regression coefficients. Hypotheses testing confirmed support for H1 and H3, while H2 was not supported in the multivariate model. Table 4.13 summarizes hypothesis testing decisions.

Table 4.10: Multiple Regression Model Summary

Model	**R**	**R Square (R^2)**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.801	0.642	0.631	0.45731

Table 4.11: ANOVA Results for Multiple Regression Model

Model Source	Sum of Squares	df	Mean Square	F-Statistic	Sig. (p-value)
Regression	34.179	3	11.393	54.477	0.000**
Residual	19.031	91	0.209		
Total	53.210	94			

Table 4.12: Multiple Linear Regression Parameter Estimates

Variable Name	Unstandardized B	Std. Error	Standardized Beta (β)	t-Value	Sig. (p-value)
(Constant)	0.219	0.322	—	0.680	0.498
Kinetic Control Efficacy (KCE - IV1)	0.365	0.102	0.318	3.580	0.001
Catalyst System Performance (CSP - IV2)	0.151	0.127	0.142	1.195	0.235
Feedstock Purity Management (FPM - IV3)	0.420	0.130	0.419	3.225	0.002

Table 4.13: Summary of Hypotheses Testing Outcomes

Hypothesis	**Hypothesized Path Relationship**	**Path Beta (β)**	**p-Value**	**Empirical Decision**
H1	Kinetic Control Efficacy (KCE) → Integrated Reactor Performance (IRP)	0.318	0.001	Supported
H2	Catalyst System Performance (CSP) → Integrated Reactor Performance (IRP)	0.142	0.235	Not Supported
H3	Feedstock Purity Management (FPM) → Integrated Reactor Performance (IRP)	0.419	0.002	Supported

5. Discussion and Implications

This chapter interprets the empirical findings in relation to the study's research objectives, existing chemical engineering literature, and theoretical frameworks. The statistical results provide robust support for the predictive model, demonstrating that Kinetic Control Efficacy, Catalyst System Performance, and Feedstock Purity Management jointly account for 64.2% of the total variance in Integrated Reactor Performance ($R^2 = 0.642, F = 54.477, p < 0.001$). Addressing Hypothesis 1, Kinetic Control Efficacy exhibited a statistically significant positive effect on Integrated Reactor Performance ($\beta = 0.318, p = 0.001$), confirming H1. This aligns directly with polymerization reactor control literature (Ghasem, 2024; Fan et al., 2023; Bi et al., 2025), proving that maintaining precise hydrogen/ethylene ratios, stable catalyst injection rates, and uniform fluidized bed temperatures prevents thermal oscillations and ensures consistent resin MFI and density specifications.

Addressing Hypothesis 3, Feedstock Purity Management emerged as the single most powerful positive predictor of Integrated Reactor Performance ($\beta = 0.419, p = 0.002$), confirming H3. This empirical finding provides strong validation for catalysis and feedstock literature (Hernández Fernández et al., 2025; Kusenberg et al., 2022; Nazarloo et al., 2024), demonstrating that rigorous removal of trace catalyst poisons (water, oxygen, CO, amines) is the primary operational prerequisite for plant stability. In contrast, addressing Hypothesis 2, Catalyst System Performance demonstrated a positive zero-order correlation ($r = 0.697$) but failed to achieve statistical significance in the multivariate regression model ($\beta = 0.142, p = 0.235$), leading to the non-support of H2. This critical finding does not imply that catalyst formulation is unimportant; rather, it reveals that in a continuous commercial plant environment, catalyst performance is highly collinear with ($r = 0.848$) and conditioned upon feedstock purity and kinetic stability. Even highly advanced catalyst systems cannot deliver target activity or selectivity if feedstock purity is compromised by trace poisons.

The theoretical implications of this study are significant. By validating a perception-based operational model, this research extends Chemical Reaction Engineering and Heterogeneous Catalysis theory beyond controlled computational domains into a socio-technical operational framework. It demonstrates that industrial reactor performance is governed by a hierarchy of constraints where feedstock purity management serves as the foundational protective layer, kinetic control provides operational stability, and catalyst capabilities are realized only when input purity and kinetics are stabilized. Practically, the findings offer actionable guidance for Ras Lanuf Company. Management must prioritize capital and operational resources toward feedstock purity infrastructure—upgrading online impurity analyzers, installing advanced guard beds, and enforcing strict supplier purity specifications (Kusenberg et al., 2022). Simultaneously, investments should strengthen automated kinetic control systems and operator training to manage hydrogen ratios and grade transitions smoothly (Ghasem, 2024).

6. Limitations and Future Research Study

Several methodological limitations should be acknowledged when evaluating the findings of this research. First, the study was conducted within a single petrochemical organization—the Ras Lanuf Company in Libya. While this provided in-depth, context-specific insights into gas-phase polyethylene operations, findings may require adaptation before generalizing to slurry or solution PE technologies, or facilities in different regulatory environments. Second, the investigation utilized a cross-sectional survey design, capturing operational perceptions at a single point in time, which inherently limits the capacity to establish multi-year longitudinal causal trends. Third, the research relied on structured technical survey instruments capturing expert perceptions rather than direct DCS continuous sensor logs or physical laboratory resin testing data. Fourth, the model examined three primary process variables, excluding potential exogenous influences such as plant electrical grid stability, mechanical equipment age, and corporate supply chain logistics.

To extend the contributions of this study, several directions for future research are recommended. First, future studies should employ multi-site comparative designs across polyolefin plants in the MENA region to enhance external generalizability. Second, longitudinal research should track reactor performance pre- and post-implementation of feedstock purification upgrades or automated kinetic control systems across multi-year operating campaigns. Third, researchers should combine perceptual survey metrics with objective, real-time Distributed Control System (DCS) data, online gas chromatography logs, and laboratory Melt Flow Index / density quality control records using Structural Equation Modeling (SEM). Fourth, future research should explore the integration of Industry 4.0 artificial intelligence, machine learning algorithms, and digital twin models (Yang et al., 2025) for real-time predictive control of feedstock impurity surges and kinetic disturbance management in fluidized bed reactors.

In conclusion, this research empirically proves that Integrated Reactor Performance in gas-phase polyethylene production is driven primarily by Feedstock Purity Management and Kinetic Control Efficacy. By establishing that catalyst system performance is conditioned upon input feed purity, this study provides Ras Lanuf Company with a clear, evidence-based operational roadmap: prioritizing feedstock purification and robust kinetic control to eliminate off-spec production, maximize operational uptime, and achieve long-term commercial excellence in polyolefin manufacturing.

References

Bi, T., Zhang, L., Wang, C., & Chen, J. G. (2025). Closed-loop recycling of polyethylene to ethylene via a kinetic-driven reactor control strategy. *Nature Reviews Methods Primers, 5*(1), Article 25. https://doi.org/10.1038/s44286-025-00290-y

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Bryman, A., & Bell, E. (2015). *Business research methods* (4th ed.). Oxford University Press.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Connelly, L. M. (2008). Pilot studies. *Medsurg Nursing, 17*(6), 411–412.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Fan, X., Sun, J., Wang, J., Huang, Z., Liao, Z., Han, G., & Yang, Y. (2023). Scale-up and thermal stability analysis of fluidized bed reactors for ethylene polymerization. *Chinese Journal of Chemical Engineering, 62*, 281–290. https://doi.org/10.1016/j.cjche.2023.03.023

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2019). *How to design and evaluate research in education* (10th ed.). McGraw-Hill Education.

Ghasem, N. (2024). Transient behavior and control of polyethylene production in a fluidized bed reactor utilizing population balance model. *International Journal of Molecular Sciences, 25*(5), Article 2602. https://doi.org/10.3390/ijms25052602

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hernández Fernández, J. A., Ortiz Paternina, K. L., & Cano-Cuadro, H. (2025). Computational study of catalytic poisoning mechanisms in polypropylene polymerization: The impact of dimethylamine and diethylamine on the deactivation of Ziegler–Natta catalysts and co-catalysts. *Polymers, 17*(13), Article 1834. https://doi.org/10.3390/polym17131834

Keith, T. Z. (2019). *Multiple regression and beyond: An introduction to multiple regression and structural equation modeling* (3rd ed.). Routledge.

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kusenberg, M., Eschenbacher, A., Delva, L., De Meester, S., Delikonstantis, E., Stefanidis, G. D., Ragaert, K., & Van Geem, K. M. (2022). Towards high-quality petrochemical feedstocks from mixed plastic packaging waste via advanced recycling: The past, present and future. *Fuel Processing Technology, 238*, Article 107474. https://doi.org/10.1016/j.fuproc.2022.107474

Lavrakas, P. J. (2008). *Encyclopedia of survey research methods*. SAGE Publications. https://dx.doi.org/10.4135/9781412963947

Nazarloo, M., Jafarian, S., & Karimi, M. (2024). Mitigating catalyst deactivation in catalytic pyrolysis of waste LDPE using an ex-situ fixed-bed reactor design. *Journal of Analytical and Applied Pyrolysis, 181*, Article 106635. https://doi.org/10.1016/j.jaap.2024.106635

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? Critique and recommendations. *Research in Nursing & Health, 29*(5), 489–497. https://doi.org/10.1002/nur.20147

Resnik, D. B. (2020). *The ethics of research with human subjects: Protecting people, advancing science, promoting trust*. Springer.

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill-building approach* (7th ed.). John Wiley & Sons.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson Education.

Yang, T., Liang, J., Qin, Y., Zhou, X., He, J., Wang, Y., Zhu, Y., Wei, Z., & Zhao, S. (2025). Machine learning-driven prediction of ethylene homopolymerization reaction performance: FI catalyst activity, polyethylene molecular weight, and molecular weight distribution. *Chemical Engineering Journal, 511*, Article 162198. https://doi.org/10.1016/j.cej.2025.162198